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Algorithm Based on Grey Clustering and Shannon Entropy to Assess Landscape Visual Quality

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***Abstract*—Landscape assessment has been limited to methodologies with subjective and qualitative approaches, due to prevailing the concept of landscape as the perception of territory. In this work, the intrinsic visual quality of the landscape was evaluated using an algorithm based on grey clustering and Shannon entropy. The grey clustering method was used to determine the landscape visual quality, and Shannon entropy was applied to calculate wights of criteria used for evaluation. The case study was performed on mining project located in Cajamarca, Peru, where three landscape units were identified and four evaluation criteria were established, before and after the implementation of project. The results revealed that there is a notable effect of the change in landscape visual quality in three evaluated landscapes units. The criteria in order of evaluation were the intrinsic visual quality of the water, relief, vegetation cover, and artificial elements. Consequently, the method showed quantitative and qualitative results that could help the landscape assessment process to make better decisions regarding mining projects.**

***Keywords*—Grey clustering, Landscape visual quality, Mining project, Shannon entropy.**

I. INTRODUCTION

Landscape is the spatial and visual expression of the territory and is defined as the sensory and subjective perception of the environment [1]. It is also considered as a natural and cultural resource that is depreciated by human activity and is difficult to renew [2]. There are several methodologies for evaluating the landscape visual quality, many of which have a subjective approach that may differ depending on the criteria used or the measurement systems considered. It can be summarized that landscape studies are based on considerations of subjectivity in the valuation of landscape and use of various techniques, whether automatic or not, for the valuation and classification of the landscape [3] [4].

Overall, landscape assessment identifies the main components or elements of the landscape and studies the set of interrelationships between geomorphology, climate, vegetation, fauna, water, and anthropogenic modifications [5]. The mining activity is a source of negative impacts to the environment, among these the landscape resource is highlighted [6], these can be expressed in modifications in topography; loss, erosion, and contamination of soils; loss of vegetation; degradation of surface water quality; among others [7]. The Yanacocha mine, of the open pit type, is mainly dedicated to the extraction of gold and silver. The area where it is located has been explored since the 1960s; however, it began operations in August 1993 with the execution of Carachugo project and subsequently Maqui Maqui (1994), Cerro Yanacocha (1997), La Quinua (2001) and Cerro Negro (2003) projects came into operation [8].

In this work, the visual quality of the landscape in area of influence the Yanacocha mining project was analyzed by applying an algorithm based on the grey clustering method and the Shannon entropy. On the one hand, grey clustering is a method that divides a series of objects according to the grey incidence matrix or the Center Point Triangle Whitenization Weight Functions (CTWF) [9], these functions allow determining the relevance of objects to predetermined classes, obtaining results that could be more reliable as they are supported by fuzzy logic [10]. On the other hand, the Shannon entropy theory is applied in the measurement of contrast between criteria [11], method developed by Claude E. Shannon [12].

The objective of this study is to apply an algorithm based on the grey clustering method, specifically Center Point Triangle Whitenization Weight Functions (CTWF), and Shannon entropy. The analysis is complemented with the application of a percentage system to assess effect of the change in intrinsic visual quality of the landscape units of the mining project both before and after its implementation.

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In this paper, in the Section II, details of algorithm based on the grey clustering method and Shannon entropy are presented. Then, Section III presents the description of case study, followed by the results and discussion in Section IV. Finally, conclusions are provided in Section V.

II. METHODOLOGY

The analysis was carried out using the grey clustering method, which divides a series of objects according to the grey incidence matrix or the Whitenization functions corresponding to predetermined classes. In this work, the procedure of Center Point Triangle Whitenization Weight Functions (CTWF) was used [10]. In addition, an evaluation of criteria weights was carried out by the Shannon entropy method, which was used for decision making related to the improvement of visual landscape quality of the project. The schema of algorithmbased on the grey clustering method and Shannon entropy is presented in Fig. 1.

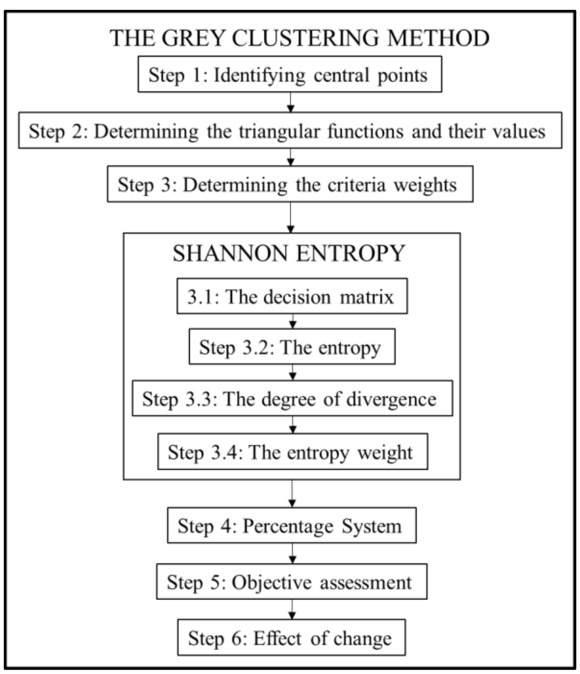

Fig. 1.Algorithm based on the grey clustering method and Shannon entropy

A. Algorithm based on the grey clustering method and Shannon entropy

In this instance, the procedure from the algorithm proposedin this work is developed by the following steps [13] [14]:

1) Step 1: Identifying central points: The criteria intervals are divided into “s” grey classes, and then their central values are obtained for each of them as follows: λ_1, λ_2, . . ., and λ_s.

2) Step 2: Determining the triangular functions and their values: The triangular functions were formed from the grey classes determined.

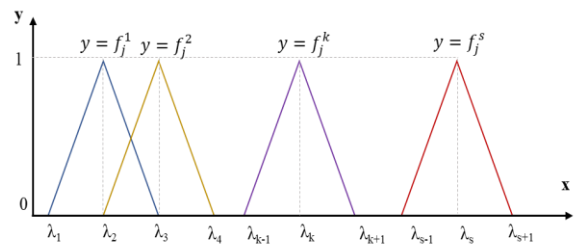

Fig. 2. Center-point triangular whitenization weight functions

$$f_k^j(x_{ij}) = \begin{cases} 0, x \notin [\lambda_{k-1}, \lambda_{k+1}] \\ \dfrac{x-\lambda_{k-1}}{\lambda_k-\lambda_{k-1}}, x \in [\lambda_{k-1,}\ \lambda_k] \\ \dfrac{x-\lambda_{k-1}}{\lambda_k-\lambda_{k-1}}, x \in [\lambda_{k,}\ \lambda_{k+1}] \end{cases} \qquad (1)$$

3) Step 3: Determining the criteria weights: The weight for each criterion was determined using the Shannon entropy method, which has the following steps:

Step 3.1: The decision matrix $Z = z_{ij}$; i =1, 2, ..., m; j = 1, 2, ..., n was standardized for each criterion C_j (j = 1, 2, ..., n). The normalized values Pij were calculated using Eq. 2.

$$P_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}} \qquad (2)$$

Step 3.2: The entropy Hj of each criterion Cj was calculated using Eq. 3.

$$H_j = -k \sum_{i=1}^{m} P_{ij} \ln(P_{ij}) \qquad (3)$$

$Where: k = (\ln(m))^{-1}$

Step 3.3: The degree of divergence div_j of the intrinsic information in each criterion C_j was determined by Eq. 4.

$$div_j = 1 - H_j \qquad (4)$$

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Step 3.4: The entropy weight w_j of each criterion C_j was calculated by Eq. 5.

$$\omega_j = \frac{div_j}{\sum_{j=1}^{n} div_j} \tag{5}$$

4) Step 4: Percentage System: The CTWF values were presented as a percentage system defined in s values $\alpha_1, \alpha_2, \ldots, \alpha_s$ in which $\alpha_s = 100, \alpha_1 = 100/s, \alpha_2 = \alpha_1 + \alpha_1, \alpha_3 = \alpha_1 + \alpha_2, \ldots,$ and $\alpha_{s\ 1} = \alpha_1 + \alpha_{s\ 2}$. The results for each object evaluated are calculated by Eq. 6.

$$z_j^i = \sum_{k=1}^{s} f_j^k\left(\chi_{ij}\right) . \alpha_k \tag{6}$$

Where: f_k (x_{ij}) is the CTWF value of the kth grey class of the j_{th} criterion and αk is the percentage value of each grey class.

5) Step 5: Objective assessment: Objective assessments Q_i^k were determined for the object *i*, *i* = 1, 2, . . ., *m*, using Eq. 7.

$$Q_i^k = \sum_{j=1}^{n} z_{ij} . \omega_j \tag{7}$$

6) Step 6: Effect of change: the effect of change on landscape visual quality (*E*) was determined by Eq. 8.

$$E = \frac{Q_i^k(before) - Q_i^k(after)}{Q_i^k(before)} . 100\% \tag{8}$$

III. Case Study

The landscape visual quality assessment carried out in a mining project located in the department of Cajamarca in Peru (see Fig. 3), which encompasses an area of 125km2. The mining project began operations in 1993.

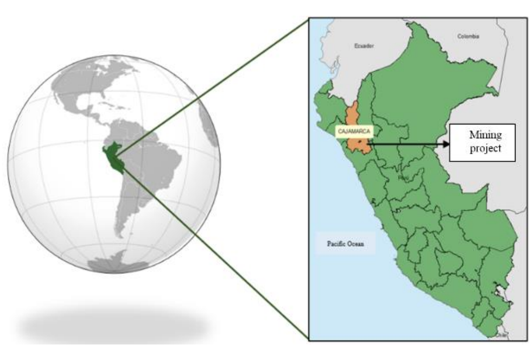

Fig. 3. Location map of the mining project

A. Study Objects Definition

Three study objects, landscape units, were defined in thecase study, which are presented below:

1) *Upper watershed of Alto Marañón (G1):* The sector of the river called Alto Marañón is located between its source, in the Nevada of Raura, and the Pongo of Manseriche.
2) *Upper-middle watershed of Jequetepeque (G2):* The middle and upper watersheds of Jequetepeque extend from 2,000 to 4,200 meters above sea level. In the upper part of the watershed (>3,500 meters above sea level) there are approximately 36,000 hectares of natural mountain forests.
3) *Upper-middle watershed of Crisnejas (G3):* Crisnejas River owes its origin to rivers that rise around 4,000 meters above sea level, being the main ones Cajamarca, Mashoon, Namora and Condebamba.

B. Evaluation criteria definition

Four evaluation criteria were defined in the case study, which are presented below:

1) *Intrinsic visual quality of the relief (C1):* The intrinsic visual quality of the relief refers to the physiographic and morphological characteristics of each landscape unit, whose evaluation depends on the presence of geomorphological singularities, the degree of its vertical development and its topographical complexity.
2) Intrinsic visual quality of the vegetation (C2): The intrinsic visual quality of the vegetation considered the land uses and the vegetation cover present in each landscape unit to be analyzed. This index was obtained for each type of vegetation or soil occupation present in each landscape unit, through the average of the following factors: First, Physiognomy (p), which refers to the visual characteristics of the external forms of the dominant vegetation such as size and foliage.
3) Intrinsic visual quality of water (C3): The intrinsic visual quality of the water considered the criteria presented in Table 5, which has a range of scores from 1 to 4. The assessment is related to the presence or absence of water bodies and the way they manifest themselves; the highest score is given to the presence of lentic bodies of water and unique elements (like waterfalls, among others).
4) Intrinsic visual quality of artificial elements (C4): The intrinsic visual quality of the artificial elements is a function of the surface occupied, the degree of integration or discordance of these elements with the landscape.

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Then, the values of criteria were obtained using georeferenced information obtained from the government of Peru through GeoGPS Peru, EVA SENACE's computer platform, and applying calculations from residual landscape impact. The results before and after of mining project are presented in Table I.

Table I.
Values Of Criteria Before And After Of Mining Project

Object	Before				After			
	C1	C2	C3	C4	C1	C2	C3	C4
G1	1.933	1.499	3.107	4	0.387	0.439	0.621	0.504
G2	1.905	1.583	3.212	4	0.381	0.424	0.642	0.584
G3	2.127	1.506	3.681	4	0.425	0.681	0.736	0.250

C. Grey classes definition

In the case study, based on the methodology described [17],six grey classes were determined for the visual quality of the landscape. Then, the six grey classes that were determined were: S1 = Low, S2 = Medium-low, S3 = Medium, S4 = Medium-high and S5 = High and S6 = Very high. These grey classes are presented in Table II.

Table II.
Grey Classes For Landscape Quality Assessment

Criteria	S1	S2	S3	S4	S5	S6
C1	0-1	1-1.5	1.5-2	2-2.5	2.5-3	3-4
C2	0-1	1-1.5	1.5-2	2-2.5	2.5-3	3-4
C3	0-1	1-1.5	1.5-2	2-2.5	2.5-3	3-4
C4	0-1	1-1.5	1.5-2	2-2.5	2.5-3	3-4

D. Calculations using the algorithm proposed

The calculations for the case study, based on the steps of the algorithm based on the grey clustering method and Shannon entropy, were preceded as follow:

1) Step 1: From Table II, the center-point values of each grey classes were determined. The values are shown in Table III.

Table III
Center-Points Of Grey Classes

Criteria	S1	S2	S3	S4	S5	S6
C1	0.5	1.25	1.75	2.25	2.75	3.5
C2	0.5	1.25	1.75	2.25	2.75	3.5
C3	0.5	1.25	1.75	2.25	2.75	3.5
C4	0.5	1.25	1.75	2.25	2.75	3.5

2) Step 2: In this step, the values presented in Table III were substituted in Eq. 1, to obtain the CTWF of six grey classes. Then, values from Table I were replaced in the CTWF to obtain values of each criterion. As an example, the results for G1 object before the project are shown in Table IV.

Table IV.
CTWF Values For Object G1

Functions	C1	C2	C3	C4
$f_1(x)$	0	0	0	0
$f_2(x)$	0	0.501	0	0
$f_3(x)$	0.635	0.499	0	0
$f_4(x)$	0.365	0	0	0
$f_5(x)$	0	0	0.524	0
$f_6(x)$	0	0	0.476	1

In turn, the values of all criteria were obtained using the same procedure.

3) Step 3: In this step, the Shannon entropy steps were applied.

Step 3.1: The decision matrix Z was standardized for each criterion C_j (j = 1, 2, 3, 4). As an example, from Table I, with data before project, the normalized values P_{ij} were calculatedby equation Eq. 2. The results are presented in Table V.

Table V.
Standardized Values For Values Before Project

Objects	C1	C2	C3	C4
G1	0.324	0.327	0.311	0.333
G2	0.319	0.345	0.321	0.333
G3	0.357	0.328	0.368	0.333

Step 3.2: The entropy H_j of each criterion C_j is calculatedusing Eq. 3. Results are provided in Table VI.

Step 3.3: The degree of divergence div_j of the intrinsic information in each criterion C_j is estimated by Eq. 4. The results are presented in Table VI.

Step 3.4: Entropy weight w_j *of* each criterion C_j is calculated by Eq. 5. The results are presented in Table VI.

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Table VI.
H_j, div_j, AND w_j VALUES

Values	C1	C2	C3	C4
H_j	0.9986	0.9995	0.9972	0.9997
div_j	0.0014	0.0005	0.0028	0.0003
w_j	0.2766	0.1095	0.5609	0.0530

4) Step 4: For the evaluation of landscape quality the case study, a percentage system was used defined by the values: α1, α2, α3, α4, α5 and α6; where α6 = 100, α1 = $\frac{100}{6}$ = 16.67, α2 = α1 + α1 = 33.33, α3 = α1 + α2 = 50, α4 = α1 + α3 = 66.67 and α5 = α1 + α4 = 83.33; according to six established grey classes, as shown in Table VII.

Table VII.
Percentage System Values

Land scape visual quality	Range	α_k
Low	[16.67, 25]	16.667
Medium Low	[25, 41.67]	33.333
Medium	[41.67, 58.34]	50.000
Medium High	[58.34, 75]	66.667
High	[75, 91.67]	83.333
Very high	[91.67,100]	100.000

Now, from Table IV, as an example for G1 object before project, the results of the percentage system, using Eq. 6, are presented in Table VIII.

Table VIII.
Percentage System Values For G1 Before Project

Functions	C1	C2	C3	C4
$f_1(x)$	0	0	0	0
$f_2(x)$	0	16.702	0	0
$f_3(x)$	31.735	24.946	0	0
$f_4(x)$	24.353	0	0	0
$f_5(x)$	0	0	43.693	0
$f_6(x)$	0	0	47.568	100
Total	56.088	41.649	91.261	100

5) Step 5: Then, the objective assessment, as an example, forG1 object before the project, from Table VI and Table VIII, were calculated using Eq. 7. Then, the results for all objectsare shown in Table IX.

Table IX.
Values Of Criteria Before And After Of Mining Project

Object	Befor e				
	C1	C2	C3	C4	Total
G1	56.088	41.649	91.261	100	76.564
G2	55.170	44.447	93.602	100	77.929
G3	62.558	41.880	100	100	83.280
Object	After				
	C1	C2	C3	C4	Total
G1	16.667	16.667	19.363	16.744	18.183
G2	16.667	16.667	19.832	18.541	18.541
G3	16.667	20.684	21.916	16.667	20.051

6) Step 6: Finally, from Table IX, the effect of change onlandscape visual quality (E) was determined using Eq. 8 and then, these results were classified according to values from Table X. Results for each object are presented in Table XI.

Table X.
Classification Range

Valuation	Variation interval (%)
No effect	[16.67, 25]
Slightly significant	[25, 41.67]
Significant	[41.67, 58.34]
Very significant	[58.34, 75]
Remarkable	[75, 91.67]
Very remarkable	[91.67,100]

Table XI.
Standardized Values

Objects	Before	After	Impact effect	Valuation
G1	76.564	18.183	76.25%	Remarkable
G2	77.929	18.541	76.21%	Remarkable
G3	83.280	20.051	75.92%	Remarkable

IV. Results And Discussion

A. About the case study

The landscape visual quality assessment of three landscape units (objects) of the mining project generated the following results:

Firs, according to the methodology used, it was observed that the landscape visual quality decreased from the mining project activities in the three landscape units. The effect of change in landscape visual quality in G1 was 76.25%, whilein G2 was 76.21%, and in G3 was 75.92%.

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Therefore, the implementation of the project generated a greater effect on the intrinsic visual quality of the landscape in G1, followed by G2 and G3, based on the four criteria analyzed.

Second, according to the methodology applied, the order of assessment of the criteria was C3 (intrinsic visual quality of water), C1 (intrinsic visual quality of the relief), C2 (intrinsic visual quality of the vegetation cover), and C4 (intrinsic visual quality of the artificial elements). Then, the visual quality assessment of each of the criteria analyzed before and after the implementation of the project by landscape unit is presented in the Fig. 4.

1) Intrinsic visual quality of the relief (C1): For the landscape units G1 and G2, the intrinsic visual quality of the relief before the implementation of the project presented an average evaluation corresponding to a slight slope, while G3 presented a medium-high quality corresponding to a relief with a moderate slope. However, after the implementation of the project, the quality in the landscape units decreased to a low quality, which is due to the clearing activities or others necessary for the operation of the mining project.

2) Intrinsic visual quality of the vegetation (C2): For the landscape unit G1, the intrinsic visual quality of the vegetation cover before the implementation of the project presented a low average value since the vegetation is mainly made up of Andean grasslands. In addition, the landscape units G2 and G3 presented an average value, due to the presence of other types of vegetation with a higher visual quality index such as forest plantations and shrubbery. However, after the implementation of the project, the quality of the three landscape units decreased to a low quality, since a large extension of Andean grasslands was transformed into mining areas.

3) Intrinsic visual quality of water (C3): For the landscape unit G1, the intrinsic visual quality of the water presented a high valuation, while G2 and G3 presented a very high valuation, this is because in all the landscape units the presence of rivers, streams, lakes, and lagoons was observed. Nevertheless, G3 presented better quality because it occupied a relative area of lakes and lagoons of 68.11%, followed by G2 and G1 which presented a relative area of 21.21% and 10.68% respectively. Moreover, after the implementation of the project, the intrinsic visual quality of the water was low in all three landscape units since the mining project site area was developed over the areas where the water bodies were located.

4) Intrinsic visual quality of artificial elements (C4): For the three landscape units, the intrinsic visual quality of the artificial elements presented a very high valuation, this due to the absence of artificial elements that could affect the visual quality. However, after the implementation of the project, the quality was low due to the presence of artificial elements, such as roads, houses and mining infrastructure, the latter being the most significant. Among them, G2 had the lowest quality since 75.06% of its extension was occupied with artificial elements, followed by G1 with 70.21% and G3 with 54.97%.

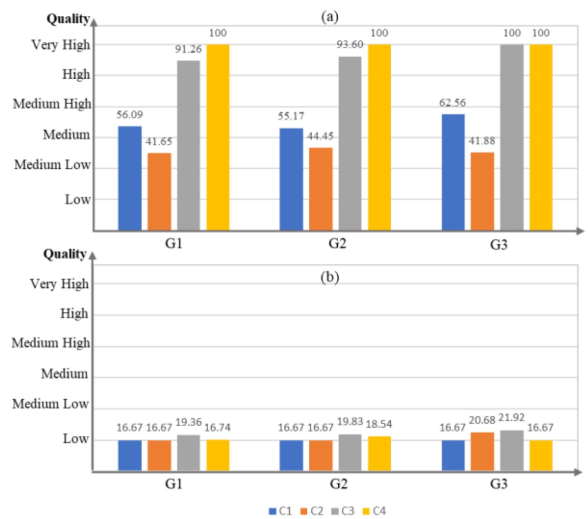

Fig. 4. Objective evaluation by landscape unit: Before(a), After(b)

B. About the Methodology

The evaluation of intrinsic visual quality is a subject with a high level of uncertainty, which requires to be studied by a method that considers the uncertainty within its analysis. Therefore, the algorithm based on the grey clustering method and Shannon entropy has an advantage [13, 14].

Furthermore, the grey clustering method considers a clear extension for the evaluation criteria, unlike other classical methods. Likewise, the weighting of the criteria by the Shannon entropy method stands out from methods such as Delphi [15] or AHP [16, 17] since these methods assume the degrees of importance or assessment of the criteria to be studied. However, a limitation of the integrated method is that the methods of grey clustering and Shannon entropy are not widely disseminated and developed as other statistical methods of classical approach are [18].

V. CONCLUSION

The determination of the intrinsic visual quality of the landscape was done by applying of algorithm based on the grey clustering method and Shannon entropy, which allowed the assignment of weights for each of the criteria. The results obtained of the intrinsic visual quality both before and after the implementation of the mining project would allow the mining company and appropriate authorities to be aware of and decide on the effect of the change caused by the mining activities.

The grey clustering method and Shannon entropy provide advantages over other multicriteria analysis methods, due to the consideration of uncertainty within their analysis. However, they present disadvantages such as the little diffusion in comparison with fuzzy logic multicriteria analysis methods and the difficulty of calculations; however, this disadvantage can be overcome with the development of computer software.

Finally, the algorithm used in this study could be applied to future evaluations of the intrinsic visual quality of the landscape caused by the activities of different projects. Likewise, it can be used as part of the landscape impact assessment, which considers the additional analysis of the visual impact of the alterations produced by the implementation of mining activity.

REFERENCES

[1] R. Amaral, G. M. M. Baptista and M. C. L. Bezerra, "Indentifying Carbon Sinks Whith the Use of Hyperspectral Images: A Potencial Tool for Ladscape Planning," 2020 IEEE Latin American GRSS and ISPRS Remote Sensing Conference (LAGIRS), 2020, pp. 254-258, doi:10.1109/LAGIRS48042.2020.9165595.

[2] A. Jain, O. Saborio-Romano, J. N. Sakamuri and N. A. Cutululis, "Virtual Resistance Control for Sequential Green-start of Offshore Wind Power Plants," in IEEE Transactions on Sustainable Energy, 2022, doi: 10.1109/TSTE.2022.3159620.

[3] A. Delgado, A. Aguirre, E. Palomino and G. Salazar, "Applying triangular whitenization weight functions to assess water quality of main affluents of Rimac river," 2017 Electronic Congress (E-CON UNI),2017, pp. 1-4, doi: 10.1109/ECON.2017.8247308.

[4] A. Delgado and I. Romero, "Environmental conflict analysis on a hydrocarbon exploration project using the Shannon entropy," 2017 Electronic Congress (E-CON UNI), 2017, pp. 1-4, doi: 10.1109/ECON.2017.8247309.

[5] C. Wang, "Intelligent System of Green Urban Garden Landscape Design Based on VR and Multi-Dimensional Image Mining," 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), 2022, pp. 864-867, doi: 10.1109/ICAIS53314.2022.9742862.

[6] A. Delgado and I. Romero, "Applying the Grey Systems Theory to As- sess Social Impact from an Energy Project," 2018 IEEE XXV Interna- tional Conference on Electronics, Electrical Engineering and Computing (INTERCON), 2018, pp. 1-4, doi: 10.1109/INTERCON.2018.8526372.

[7] K. Prag, M. Woolway and T. Celik, "Toward Data-Driven Optimal Control: A Systematic Review of the Landscape," in IEEE Access, vol. 10, pp. 32190-32212, 2022, doi: 10.1109/ACCESS.2022.3160709.

[8] I. Chambefort, J. H. Dilles and A. A. Longo, "Amphibole Geochemistry of the Yanacocha Volcanics, Peru: Evidence for Diverse Sources of Magmatic Volatiles Related to Gold Ores," in Journal of Petrology, vol.54, no. 5, pp. 1017-1046, May 2013, doi: 10.1093/petrology/egt004.

[9] A. Delgado, P. Montellanos and J. Llave, "Air quality level assessment in Lima city using the grey clustering method," 2018 IEEE InternationalConference on Automation/XXIII Congress of the Chilean Association of Automatic Control (ICA-ACCA), 2018, pp. 1-4, doi: 10.1109/ICA- ACCA.2018.8609699.

[10] S. Liu, C. Lin and Y. Yang, "Several problems need to be studied in grey system theory," 2017 International Conference on Grey Systems and Intelligent Services (GSIS), 2017, pp. 1-4, doi: 10.1109/GSIS.2017.8077658.

[11] S. Torene and B. Howald, "Automated Hashtag Hierarchy Generation Using Community Detection and the Shannon Diversity Index," 2022 IEEE 16th International Conference on Semantic Computing (ICSC), 2022, pp. 59-66, doi: 10.1109/ICSC52841.2022.00016.

[12] M. Zhou, "A Theory on AI Uncertainty Based on Rademacher Com- plexity and Shannon Entropy," 2020 IEEE 3rd International Conference of Safe Production and Informatization (IICSPI), 2020, pp. 24-27, doi: 10.1109/IICSPI51290.2020.9332424.

[13] F. Lyu and Y. Zhu, "The Evaluation Model of Enterprises' Digital Transformation Competence Based on the Grey Cluster Method," 2021 IEEE International Conference on Industrial Engineer- ing and Engineering Management (IEEM), 2021, pp. 533-537, doi:10.1109/IEEM50564.2021.9673079.

[14] W. Huang, X. Chuai, Y. Rao and B. Li, "Shannon Entropy-Based Seis- mic Local Correlation Measure and Enhancement," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 3000905, doi: 10.1109/LGRS.2020.3038232.

[15] A. K. Shah, A. Bahadur Singh, A. Dahiya and U. Soni, "Time Series Prediction of PM 2.5 Level in Delhi," 2019 International Conference on Computing, Power and Communication Technologies (GUCON), 2019,pp. 792-795.

[16] S. Dutta, D. R. Dange, T. Chakraborty and M. Majumder, "A Fuzzy AHP Approach for Prioritization of Parameter for Hybridization of Renewable Sources," 2022 IEEE Delhi Section Conference (DELCON), 2022, pp. 1-4, doi: 10.1109/DELCON54057.2022.9753588.

[17] A. Delgado and H. Flor, "Selection of the best air purifier system to urban houses using AHP," 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), 2017, pp. 1-4, doi: 10.1109/CHILECON.2017.8229622.

[18] Li, Y., Niu, Y., Wang, W., and Li, B. (2017). Grey-incidence clustering decision-making method with three-parameter interval grey number based on regret theory. Paper presented at the 2017 IEEE International Conference on Grey Systems and Intelligent Services, GSIS 2017, 211-218. doi:10.1109/GSIS.2017.8077706